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Modelling fire occurrences in heavy goods vehicles in road tunnels

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ABSTRACT

The project reported in this paper has been organized to scrutinize current incident data on near fires and fully developed fires in Norwegian road tunnels longer than 500 m. This length is chosen because it is assumed that shorter tunnels are less critical in case of fires. The project included collecting data and transferring it into formats enabling mathematical modelling. The major issue of this work has been to resolve: What are the major contributing tunnel infrastructure factors leading to heavy goods vehicle (HGV) fires in Norwegian tunnels? By using Poisson regression modelling, several models are developed showing good fit with the observations. All models reveal that slope, length, annual average daily traffic of heavy goods vehicles, and whether a tunnel is subsea are significant factors. The most important is the subsea factor, and the effect of other risk factors is also more severe for subsea tunnels. The work also discusses weaknesses in the data material and the fact that there are several other interesting factors, for example related to the state of HGVs and driver behavior that are currently missing. The research potential for better modelling and understanding of HGV fires in tunnels is huge.

1. Introduction

The work presented in this paper assesses fire incidents in Norwegian road tunnels [1]. The regulation regime for tunnel designs is developed from the EU Directive [2], which assumes risk-informed decisions. This means that there must be underlying functional requirements describing what is to be achieved, which is in line with internationally recommended approaches [3].

1.1. Framing the issue

Norway has more than 1200 road tunnels, which have been erected and operational since 1891 (Eidfjord tunnel), and there are still many tunnels under construction. Their designs vary from single-tube “black holes” to dual-tube fully equipped tunnels addressing high quality safety measures. Tunnels are elements of the road transport infrastructure in Norway, which also varies in quality. However, Norway is amongst the safest countries in the world when we regard the occurrence of traffic accidents termed Vision Zero accidents [4]. These accidents are characterized by fatalities or seriously injured victims. These terms for recording incidents are internationally agreed upon. However, careful considerations are recommended. Elvik and Mysen [5] have documented weaknesses in the reporting systems, with regard to whether incidents are actually reported as they should be. The police are responsible for reporting incidents on roads involving injuries to road-users.

Statistics of incidents in tunnels encompassing near fires and fires in heavy goods vehicles (HGVs) should also be carefully considered. The fire departments are responsible for the reporting, using a report system that has been exposed to changes over the last ten years. In order to improve the statistics, the Norwegian Public Roads Administration (NPRA) launched studies to map the fire incidents in Norwegian tunnels [6,7]. Njå [8] assessed Nævestad et al.‘s [7] data on fires in tunnels with serious outcomes. The serious outcome events included collisions leading to fires and major consequences to humans. He identified heavy fire loads (heat release rate – HRR) for seven events, of which the fire in the Brattli tunnel lasted for several days and the Skatestraum tunnel fire was estimated at more than 400 MW. A design fire in a bus is defined as 30 MW and a truck on fire 50–100 MW [9]. Only a fire in the Follo tunnel included a fatality, with uncertainties regarding whether the victim died from smoke intoxication or from the collision forces (truck against the tunnel wall at the entrance to the tunnel). All the other fires did not include fatalities. Many road users have been seriously injured, but this information is scarce.

Norway has not seen major fires as witnessed in Europe approximately 20 years ago (Mont Blanc, Tauern and St. Gotthard tunnels).

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Nevertheless, since 2011, Norway has experienced a number of HGV fires, which, under different circumstances, very easily could have developed into cascading events as seen in Europe. Njå and Kuran studied the 2011 fire in the Oslofjord tunnel [10]. The tunnel geometry was a direct cause of the occurrence of the event (steep slopes and unfortunate driving behavior of the HGV driver). Furthermore, the tunnel system complicated rescue and evacuation, mainly related to fire ventilation, combined with a lack of road-user information. Many road-users became rapidly engulfed in heavy smoke. The researchers claimed that tunnel fire safety should be improved in Norway, based on the various characteristics of the tunnel designs and operations that emerged, such as:

- It takes too long time before road-users realize dangerous situations in tunnels and prepare for self-evacuation.
- The organizing of self-evacuation is arbitrary and, only to a limited extent, adapted for the road-users' needs.
- Road-users do not possess knowledge of tunnel fires.
- Knowledge of fire dynamics, heat development and smoke dispersion in tunnels is weak.
- Easily accessed information about Norwegian road tunnels and fire protection strategies is lacking.
- The buyers of transport services, transport salesmen, forwarding agents, transport companies and drivers of HGVs containing large amounts of energy have been very little considered and scrutinized, with respect to their roles and responsibilities regarding major fires in tunnels.
- The individual victims' post traumas and stresses have not been studied and sufficiently taken into consideration.

Based on the enforced self-regulation principle [11,12], the NPRA is deemed responsible for the tunnels (infrastructure) being safe and providing sufficient aid to safely egress within the time frame of smoke intoxication. This did not happen in the Oslofjord tunnel, and the NPRA was harshly criticized by the Accident Investigation Board Norway [13] for their lack of risk management. Understanding the HGV fire frequencies as a function of the tunnel infrastructure parameters is thus of major importance. We assume that the conditions of HGV vehicles and the performance of drivers are evenly distributed over all tunnels in Norway. This study was set up to identify connections between fire occurrences in HGVs and infrastructure variables.

1.2. Introduction to heavy goods vehicles seen from a fire occurrence perspective

Fires are always caused by a compound of several factors that include how the systems are operated, maintained and constructed. Design weaknesses are also part of this. For example, there might be spaces between the carrier and the engine room that enable easily ignited substances to enter the engine room.

Defective brakes on some shafts/wheels introduce instabilities, which are a fire hazard. Personnel in the transport industry claim that many of the foreign HGVs coming to Norway are not fit for purpose with respect to both the designs (e.g. two-axle, tires) and the maintenance level. However, the situation seems now to have improved amongst foreign HGVs, meaning that these risk predictions are more uncertain.

Most trucks use diesel engines, due to their superior power efficiency. The introduction of eco-diesel has lowered the ignition temperature, which represents an increased fire hazard from leakages. Electronic fuel injection increases accuracy and optimizes the working loads of the engines. Lube oil and cooling systems both ensure that the engine operates within tolerable limits and avoids high temperatures. Malfunctions, wear and failures in these systems have provided fire occurrences, either as hot surfaces igniting fuel material in its surroundings or sudden damage leading to breakages of pipes and hoses containing substances that ignite at lower temperatures. The exhaust systems contain gas in elevated temperatures, which is also a hazard if there are malfunctions in the insulation design. In addition to traditional petrol-based engines, new fuel systems, for example based on ammonia and hydrogen, will change the current challenges seen in HGV fires.

The electrical systems are a fire hazard, whether from erroneous use, from damaged insulation or junctions or from components such as the dynamo. The engine room is filled with polymer-based products and rubber hoses that will sustain fires once they have occurred. Leakages of hydraulic fluids, lube oils and diesel oils are critical. Some of the fuel systems contain high pressures that could worsen the situation after ignition. Fires might develop very fast.

Wheel bearings are another area that might provide heated zones and fire occurrences in tires and surrounding substances. Tires might also catch fire in certain conditions. The wheel areas containing shafts, half-shafts, sun wheels, brakes, bearings and tires are complex and need to be carefully considered as a fire hazard. A diesel storage tank of approx. 500 L also contribute to the risk image of fire occurrences in HGVs.

1.3. The need to model tunnel characteristics leading to HGV fires

The potential for severe accidents (>5 fatalities) stems from HGV fires not being controlled and containing toxic substances released from either dangerous goods or fire effluents. The fire ventilation strategy for Norwegian tunnels is longitudinal, with velocities of 3 m/s and higher. This means that smoke that includes toxic fire effluents travels fast and exposes road-users to difficult situation awareness and the requirement for fast evacuation performance. The airflow is from the tunnel entrance, where we find the best fit and equipped fire department, regardless of where in the tunnel the fire occurred. The two fires in the Gudvanga tunnel (2013 and 2015 [14,15]) both included transport of smoke over large sections, more than 8 km. Some victims were engulfed in smoke for approximately 90 min before reaching the entrance or being rescued by first responders.

Exposure to toxic fire smoke and gases [16] causes injuries and deaths in fires. The traditional terms for assessing the fire safety of humans are connected with the outcome of two parallel timelines. These are the time from the ignition of the fire to the development of incapacitating conditions (ASET) and the time required for tunnel users to reach a place of safety (RSET) [17,18]. When occupants become immersed in smoke, behavioral, sensory and physiological effects occur. Toxic fire effluents are responsible for most fire deaths and an increasingly large majority of fire injuries [16]. According to Lönnermark [19] and Voeltzel and Dix [20], cascading events are a strong predictor of HGV fires in tunnels being fatal.

1.4. Major issue

Current research and the state of the art regarding tunnel fire safety are mostly concerned with conditions after ignition and how the fire dynamics affect structures, equipment, and rescue and evacuation conditions [21,22]. This research yields fire dynamics, fire ventilation, evacuation systems and behavior, and fire extinguishing technologies that have been explored using various perspectives and research designs. Tunnel fire risk assessments encompass estimated fire frequencies, but these frequencies are rough estimates, mostly based on "engineering judgements"; thus, no in-depth evidence on why and how fires occur is normally included in such analyses.

Accident investigations also show very scarce solid evidence of why and how fires occur, as well as which factors contribute to the ignition and sustained fires in HGVs. This is quite odd when we consider the vast experiences with Norwegian risk management practices that emphasize knowledge-based assessments and risk-reducing measures prioritizing fire prevention. In Switzerland, at the entrances of the St. Gotthard tunnel, the tunnel owner has installed assemblies of temperature sensors monitoring hazardous conditions in HGVs before entering the tunnel.

Such measures contribute with valuable experience data as well as being a risk reducing measure. We developed the core research problem:

What are the major contributing tunnel infrastructure factors leading to HGV fires in Norwegian tunnels?

There is a need to provide better models and understanding of factors that contribute to tunnel fires. Norway is rather special, due to its many subsea tunnels that are regarded as dangerous but without clear evidence on which elements influence this assumption. This was our starting point for developing the fire occurrence modelling.

2. Incident data employed in the study

We accessed all data material available from the Norwegian Public Roads Administration (NPRA), the Institute of Transport Economics (TØI), the Directorate for Civil Protection (DSB) and the Accident Investigation Board Norway (AIBN). This material does not contain records on driver behavior or the technical conditions of the vehicles involved. Hence, the work consisted of developing models from tunnel characteristics and traffic flow. Sources of data:

- Descriptions of road tunnels and road tunnel geometry from the NPRA.
- Roadmap [23].
- Data on road tunnel fire incidents from 2001 to 2015 [6,7]. Njå [1] has adapted and extracted the relevant information from the data material for this study.

The data has been accumulated such that every road tunnel in Norway longer than 500 m is included (with the exception of a few, due to missing data). An Excel sheet of road tunnels and road tunnel geometry has been provided by the NPRA. It was the starting point used to sort and collect data on each tunnel and also to gather information about the tunnels. In total, 485 unique tunnels have been used out of the 538 tunnels in Norway longer than 500 m (at the time of the study, there were in total 1202 Norwegian tunnels). Other variables, such as slope, length and annual average daily traffic (AADT), were obtained from the NPRA's data material.

TØI's data [6,7] on fire incidents has been used to count fire and near-fire incidents in HGVs in road tunnels. If we include the cases where fire has not yet been fully developed and recorded, the data from Nævestad et al. [7] shows that on average 9.4 incidents occur in HGVs each year in Norwegian road tunnels. We stress that these are fires that have occurred without external influences, such as collisions with other vehicles or the tunnel walls. Table 1 shows the number of HGV fires and near fires that occurred each year due to technical failure.

We explored all Norwegian tunnel fire data, in order to establish models of the tunnel characteristics contributing to the frequency of HGV fires.

3. Regression model for fire occurrences in heavy goods vehicles in road tunnels

We applied Poisson regression models to analyze our data. The goal was to estimate the impact of tunnel infrastructure factors and traffic volume on the rate of developing and fully developed fire incidents in HGVs due to technical failures in road tunnels. As a well-established statistical method for analyzing count data, particularly for situations with rare events and varying exposure times as we have here, Poisson regression is well suited to this purpose. Goodness of fit was verified by residual plots.

Table 1
Fully developed fires and near fires due to technical failure in HGVs in tunnels from 2001 to 2015.

Year	Fire/near fire in HGVs	Year	Fire/near fire in HGVs
2001	1	2009	7
2002	0	2010	13
2003	7	2011	18
2004	7	2012	11
2005	6	2013	16
2006	9	2014	19
2007	3	2015	13
2008	11	**Total**	141

3.1. Variables

For each tunnel, we have gathered data on 11 different variables explained below. These are variables that we expect will influence fire accidents in road tunnels and also variables that are measurable and can be collected from available sources.

The number of fire incidents, more specifically developing or fully developed fires in HGVs in tunnels due to technical failure, is our response variable. We wish to model which factors influence the number of fire incidents. We have used TØI's data on incidents that has been collected from the years 2001–2015, see Table 1. Developing fires are also denoted near fires, and the criterion for its recordings is questionable, but we have used TØI's recordings without scrutinizing their basis.

Number of years with data is an exposure parameter, t_i, for the modelling approaches. Since the data on accidents ranges from 2001 to 2015, the number of years with data is a maximum of 15 years, depending on whether or not a specific tunnel has been in operation all these years. If, e.g., a tunnel was opened in 2011, it has only been exposed to incidents for five years.

The variable "*length*" is the length of each tunnel.

Subsea is a variable that indicates whether a tunnel is subsea or not. If a tunnel is subsea, it is coded with a value of 1 and 0 otherwise. Subsea tunnels are particularly interesting, as they tend to have an extreme geometry.

Length downward and upward are measurements of how far into the tunnel the incline descends or ascends. Since downward and upward lengths are relative to the direction of the vehicle entering a tunnel, we do not know what is up and what is down. We have therefore chosen to let the longest of the two be length up and the shortest, length down.

Slope is a variable representing the maximum slope of a tunnel. Slope downward and slope upward are average slopes downward and upward, respectively. The NPRA data on tunnel geometry has been used for both slopes and lengths.

Annual average daily traffic (AADT) is a measurement of how many vehicles drive through a tunnel on average each day. The NPRA's roadmap [23] has been used to collect data of AADT and *AADT for heavy goods vehicles*. The roadmap only shows AADT for 2017. If AADT has been changing over the years, which it presumably has, the fact that NPRA's roadmap only gives AADT for 2017 may cause an inaccuracy in the analysis. Fortunately, a recent study by TØI [9] tackles this problem by presenting AADT development for private and freight transport in Norway from 2005 to 2017.

The relative traffic work is the relation between the developments in private transport vs. freight transport. Note from Fig. 1 that private transport seems to increase steadily. In fact, personal transport increases approximately linearly. By using this linearity, we can conclude that the average AADT of personal transport from 2001 to 2015 is approximately equal to the median AADT for these years, i.e., AADT in 2008. Thus, the average total AADT is equal to the AADT for 2017 multiplied by a factor of 1.06/1.19, see Fig. 2. Annual average daily traffic for heavy goods vehicles is assumed to be approximately unchanged over time, and we will therefore use the 2017 AADT found in the NPRA's roadmap for the AADT for heavy goods vehicles.

3.2. Poisson regression

For modelling fire occurrences in heavy goods vehicles, we applied two distinct models. In the first model, we estimated incidents per tunnel

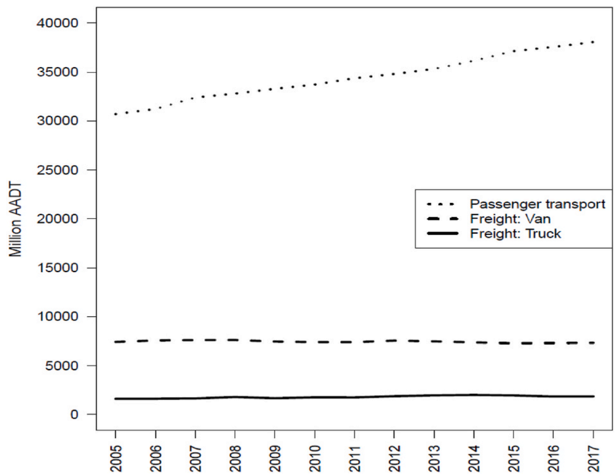

Fig. 1. AADT development for personal and freight transport in Norway from 2005 to 2017 [9].

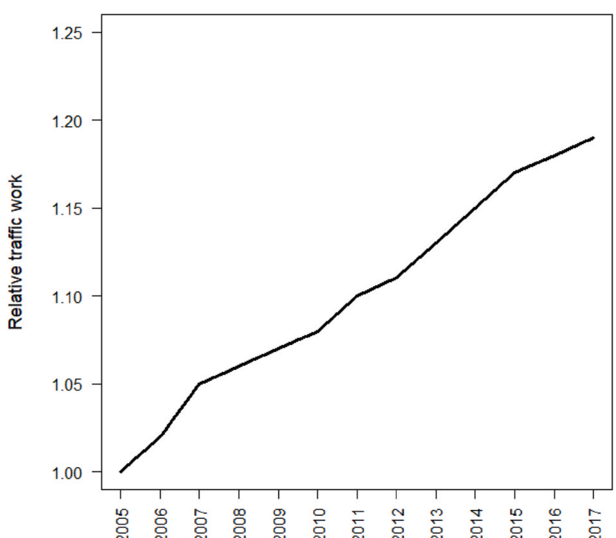

Fig. 2. Relative traffic work from 2005 to 2017 [9].

using the infrastructure and AADT variables as covariates, with "Number of years with data" as an exposure parameter. Let Y_i denote the number of fire incidents in tunnel i and let N_i be the number of years with data. Then the Poisson regression models for the expected number of incidents in tunnel i can be written:

$$E(Y_i) = N_i\lambda_i = N_i e^{\mathbf{x}_i\boldsymbol{\beta}} \tag{1}$$

where the term $\lambda_i = e^{\mathbf{x}_i\boldsymbol{\beta}} = e^{\beta_0+\beta_1 x_{1i}+\ldots+\beta_k x_{ki}}$ models how the covariates affect the rate of events λ_i. The vectors $\mathbf{x}_i = [1, x_1, \ldots, x_k]_i$ and $\boldsymbol{\beta} = [\beta_0, \beta_1, \ldots, \beta_k]^T$ are covariates (the tunnel infrastructure and traffic volume variables) and the parameters (estimated from the data), respectively. Finally N_i represents how large a fraction of the 15-year period the tunnel has been in use. Notice that we often interpret β_j in terms of e^{β_j} which is the *rate ratio* (i.e. relative increase/decrease in rate) corresponding to a one-unit increase in covariate j.

In the second model, we let the intensity λ_i describe the intensity of incidents per unit length and time, using the same covariates as before except *length*, which now is used as an exposure parameter together with *Number of years with data*.

$$E(Y_i) = L_i N_i e^{\mathbf{x}_i\boldsymbol{\beta}} \tag{2}$$

where L_i is the length and N_i is the number of years with data for each tunnel.

For all parameters, we report confidence intervals which reflect the uncertainty in the estimates due to the limited amount of data we have available. Goodness of fit was verified by plots of standardized residuals and Cook's distance plots. The analysis process was iterative and detailed but cannot be included in this paper. Further details are shown in Njå [1]. Here, we summarize some of the main results.

4. Results

For each model, we started by estimating each covariate separately in univariate models. The results for both models showed that all covariates were significant when tested separately.

We then estimated the effect of all covariates simultaneously in multiple models. Since several of the covariates are highly correlated, not all should be included in the final multiple model. We thus ran a backward elimination procedure until we ended up with only significant covariates. The results for Model 1 (incidents per tunnel) are depicted in Table 2.

From Table 2, we can see, e.g., that subsea tunnels have an estimated incidence rate which is 5.7 times higher than non-subsea tunnels and that a one-degree increase in slope increases the incidence rate by a factor of 1.13. Notice that AADT HGV is measured in units of 1000 vehicles.

By analyzing goodness of fit for the model from Table 2, we found two influential observations, see Fig. 3. These two points are marked with a circle. The points represent the Lærdal tunnel (24 km long, AADT HGV 533) and the Vålerenga tunnel (832 m long, AADT HGV 7638). Both the Lærdal tunnel and the Vålerenga tunnel have had two accidents in 15 years. Since the Lærdal tunnel is extremely long compared to other tunnels, it will receive a predicted large number of accidents relative to its observed accidents. This explains why it comes out as extreme on the residual plot.

Similarly, the Vålerenga tunnel has a high number of annual average daily traffic compared to other tunnels, giving it a predicted large number of accidents. However, the Vålerenga tunnel is not as influential as the Lærdal tunnel.

We can also plot a measure called Cook's distance versus observation number, to detect influential observations. Large values of Cook's distance may indicate that the i th observation is influential. As a general rule of thumb, Cook's distance greater than unity may require further investigation [24]. From Fig. 4, we see that the Lærdal tunnel is clearly influential. Although the Vålerenga tunnel seems to be acceptable in this plot, its Cook's distance $D_i > 1$ and may be influential..

These two plots give us a good indication that we should eliminate the Lærdal and Vålerenga tunnels from the model developed from Table 2. By doing so, we obtain the results in Table 3.

Although the residuals are not perfect, they behave much better now without these outliers (Fig. 5). We have a tail below the zero-line that mostly represents tunnels without accidents. Points above the zero-line are tunnels with accidents, and they are more spread due to the variation between observed and predicted accidents.

Table 2
Multiple model with insignificant covariates excluded; 485 tunnels included.

Variable	$\hat{\beta}$	p-value	Rate ratio (95% c.i.)
(Intercept)	−3.16	<0.001	–
Slope	0.12	0.007	1.13 (1.03–1.23)
Length[km]	0.19	<0.001	1.20 (1.17–1.24)
AADT HGV[1000]	0.57	<0.001	1.77 (1.62–1.94)
Subsea	1.74	<0.001	5.72 (3.04–10.8)

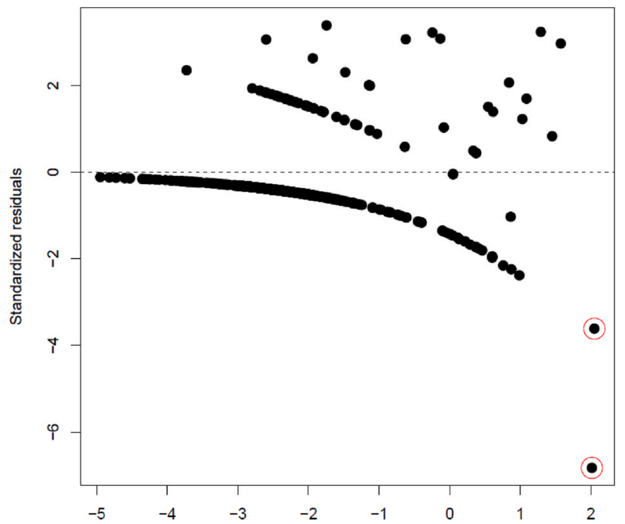

Fig. 3. Plot of standardized deletion residuals vs. $x_i\hat{\beta}$.The Lærdal tunnel and the Vålerenga tunnel are marked with red circles.

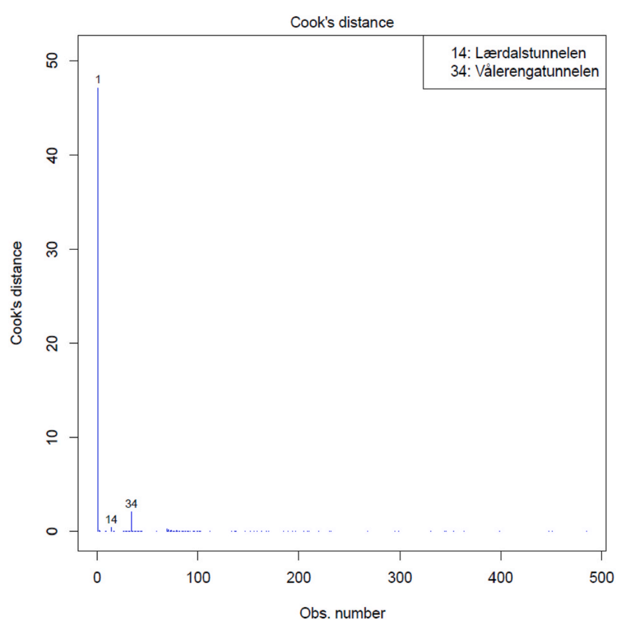

Fig. 4. Cook's distance vs. observation number.

Table 3
Multiple model with insignificant covariates and the Lærdal and Vålerenga tunnels excluded; 483 tunnels included.

Variable	$\hat{\beta}$	p-value	Rate ratio (95% c.i.)
(Intercept)	−3.61	<0.001	–
Slope	0.14	0.002	1.15 (1.05–1.25)
Length[km]	0.34	<0.001	1.41 (1.32–1.50)
AADT HGV[1000]	0.63	<0.001	1.89 (1.70–2.09)
Subsea	1.22	<0.001	3.38 (1.81–6.30)

4.1. A special case – the Ryfast tunnel

A new Norwegian subsea tunnel, called the Ryfast tunnel, is under construction. The tunnel will have a slope and length of 7% and 13.95 km, respectively. According to KS2 (the Quality Assurance study), the AADT has been estimated at 4200, of which approximately 10% will be heavy goods vehicles [25]. We tested the model for the prediction of the

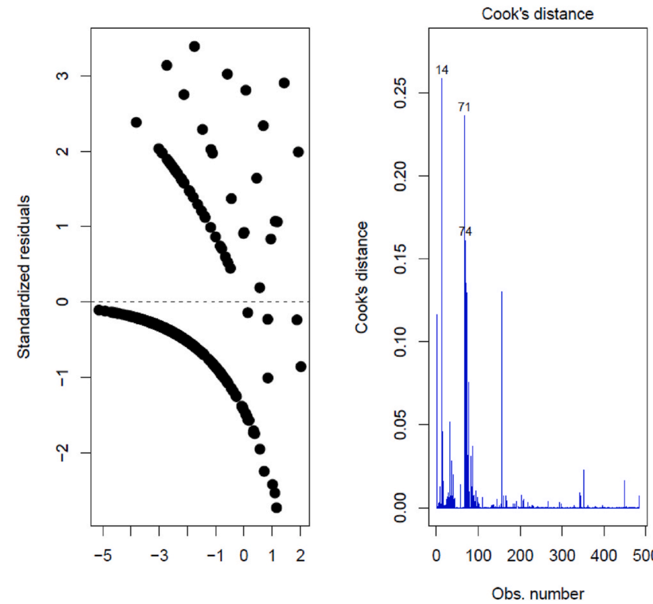

Fig. 5. Plot of standardized deletion residuals vs. $x_i\hat{\beta}$ and Cook's distance without the Lærdal tunnel and the Vålerenga tunnel.

number of accidents for this particular tunnel over the next 15 years. By using Equation (1) with estimated parameters found in Table 3, we obtained

$$E(Y) = \exp(-3.61 + 0.14 \cdot 7 + 0.34 \cdot 13.95 + 0.63 \cdot 0.42 + 1.22) = 36.51 \tag{3}$$

More than two fire incidents each year over the next 15 years seemed highly unlikely.

According to the model, the effect of length is exponential. The Ryfast tunnel is an extreme tunnel compared to other tunnels in the model. It is subsea and longer than any other tunnel in our data. With these attributes, the Ryfast tunnel would be considered an outlier in the model. However, we could try to overcome this issue by transforming one or more of the covariates by a function of the covariates' best fit, to even out these covariates, $x_i \rightarrow f(x_i)$. Polynomial and logarithmic functions are strong candidates. By analyzing the model found in Table 2, the logarithmic function seemed to be the best candidate. Transforming length and AADT produced a model that better fitted both longer and heavily loaded tunnels. Thus, we tested the model

$$\lambda_i = e^{\beta_0 + \beta_1 \log(Length) + \beta_2 \log(AADT) + \beta_3 Subsea} \tag{4}$$

With both Lærdal and Vålerenga tunnels included, this transformation yielded the results in Table 4 (see also residuals in Fig. 6).

Notice that the estimated effect of a tunnel being subsea is now reduced to the more reasonable rate increase of a factor of 1.77.

The Lærdal tunnel, which previously had a Cook's distance $D_i > 40$, was now reduced to less than 0.10. The Lærdal and the Vålerenga tunnels were no longer an issue when the effect of length and AADT HGV was not modelled as an exponential function, and these tunnels could thus be included in further modelling. The prediction of incidents in the Ryfast tunnel, using the new results from Table 4, is thus:

$$\begin{aligned} E(Y) &= \exp(-2.32 + 0.19 \cdot 7.00 + 1.15 \log 13.95 + 0.97 \log 0.42 + 0.57) \\ &= 5.87 \lim_{x \to \infty} \end{aligned} \tag{5}$$

indicating an estimate of less than six fires in the Ryfast tunnel over the next 15 years, which seems more reasonable.

The modelling for the incidents per length model (Model 2) was carried out in a similar way to that of Model 1. The results are presented

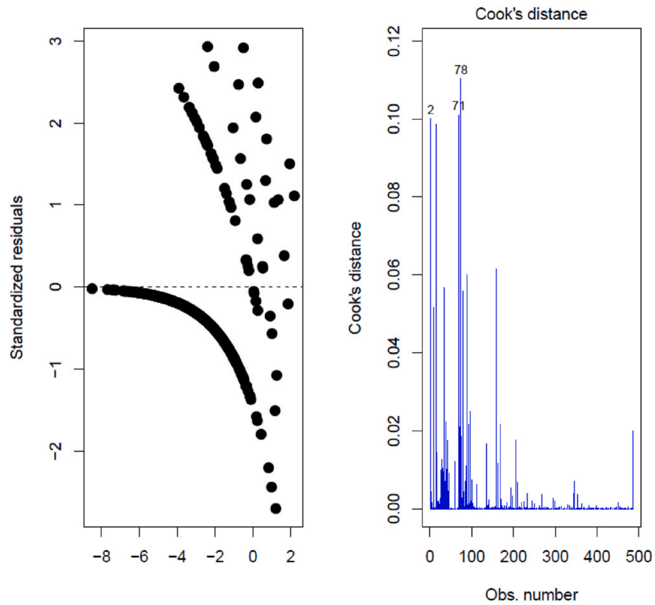

Fig. 6. Plot of standardized residuals vs. $x_i\hat{\beta}$ and Cook's distance for the model in Table 4.

Table 4
Multiple model with insignificant covariates excluded and using log-transform for length and annual average daily traffic; 485 tunnels included.

Variable	$\hat{\beta}$	p-value	Rate Rate ratio (95% c.i.)
(Intercept)	−2.32	<0.001	–
Slope	0.19	<0.001	1.21 (1.12–1.31)
log(Length[km])	1.15	<0.001	3.16 (2.50–3.99)
log(AADT HGV[1000])	0.97	<0.001	2.64 (2.24–3.08)
Subsea	0.57	0.046	1.77 (1.01–3.08)

in Table 5 (see also residuals in Fig. 7).

4.2. Sub-models

It is interesting to classify tunnels based on some properties we wish

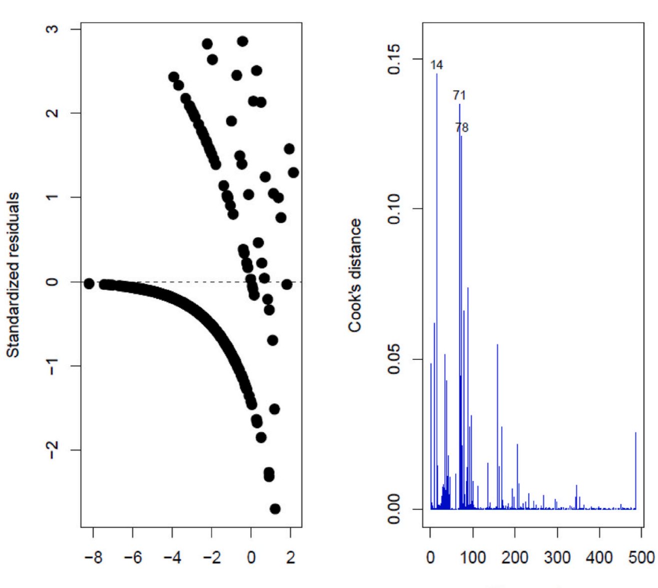

Fig. 7. Plot of standardized deletion residuals vs. $x_i\hat{\beta}$ and Cook's plot.

Table 5
Final model for the incidents per length model (Model 2); 485 tunnels included.

Variable	$\hat{\beta}$	p-value	Rate Rate ratio (95% c.i.)
(Intercept)	−2.19	<0.001	–
Slope	0.19	<0.001	1.21 (1.12–1.31)
log(AADT HGV[1000])	0.96	<0.001	2.62 (2.22–3.08)
Subsea	0.69	0.011	1.99 (1.17–3.28)

to examine and see whether the conditions are the same in subsets compared to the entire dataset. We considered various subsets of our dataset, performed regression analysis and compared the results to previous results. Since the log-transform models found in Tables 4 and 5 gave the best fit, we primarily considered these when we compared the models.

We tested "subsea versus non-subsea tunnels" and "tunnels longer than 4 km versus tunnels shorter than 4 km". The results show that the effect of AADT HGV increased for both models when including only subsea tunnels, compared to the effect of AADT HGV in the complete dataset. Moreover, the variable "subsea" is no longer significant when considering tunnels shorter than 4 km. This may indicate that the risk of fire accidents in short subsea tunnels is low.

To gain a better understanding of the results from the sub-models, we have compared them with both models by estimating parameters in univariate models. The results of Model 1 compared to various sub-models can be found in Table 6.

Notice that the effect of AADT HGV is substantially larger for subsea tunnels compared to non-subsea tunnels. Increasing annual average daily HGV traffic by 1000 in a subsea tunnel will result in an increase in the accident rate by a factor of $e^{2.38} = 10.8$, compared to $e^{0.52} = 1.68$ in a non-subsea tunnel. Furthermore, the effect of subsea for short tunnels has decreased drastically.

By comparing parameters of Model 2 and various sub-models, we obtain the results in Table 7.

Again, the effect of AADT is substantially larger for subsea tunnels.

Since some of the variables seem to have different effects for different subsets of the data, we may want to consider performing an analysis of the models, in which we include an interaction term between certain variables.

Table 6
Parameter estimates of univariate fits with Model 1 and various univariate sub-models. Significant relationship at level: ***≤0.001; ** = 0.01; * = 0.05;. = 0.1.

Variable	Model 1	Subsea	Rate Non-subsea	Rate L > 4 km	Rate L < 4 km
Slope	0.27 ***	−0.48.	0.18 **	0.34 ***	0.10.
Length [km]	0.17 ***	0.51 ***	0.14 ***	0.04	0.51 ***
log(Length)	1.26 ***	2.65 ***	0.90 ***	0.54.	1.02 ***
AADT [1000]	0.05 ***	0.28 ***	0.07 ***	0.10 ***	0.07 ***
AADT HGV [1000]	0.43 ***	2.38 ***	0.52 ***	0.55 ***	0.49 ***
log(AADT HGV)	0.68 ***	1.39 ***	0.78 ***	1.21 ***	0.70 ***
Subsea	2.34 ***	–	–	2.08 **	0.17
Slope downward	0.31 ***	0.03	0.25 *	0.31 ***	0.06
Length downward [km]	0.33 ***	1.14 ***	0.21 *	0.14	0.48
Slope upward	0.26 ***	−0.12	0.14 *	0.38 ***	0.09
Length upward [km]	0.27 ***	0.81 ***	0.25 ***	−0.11	0.50 **

Table 7
Parameter estimates of univariate fits with Model 2 and various univariate sub-models. Significant relationship at level: ***≤0.001; ** = 0.01; * = 0.05;. = 0.1.

Variable	Model 2	Subsea	Rate Non-subsea	Rate L > 4 km	Rate L < 4 km
Slope	0.21 ***	−0.51 *	0.22 ***	0.37 ***	0.08
AADT [1000]	0.07 ***	0.28 ***	0.08 ***	0.11 ***	0.07 ***
AADT HGV [1000]	0.49 ***	1.92 ***	0.56 ***	0.57 ***	0.51 ***
log(AADT HGV)	0.80 ***	1.15 ***	0.89 ***	1.25 ***	0.73 ***
Subsea	1.51 ***	–	–	2.23 **	−0.54
Slope downward	0.21 ***	0.04	0.23 *	0.32 ***	−0.02
Slope upward	0.24 ***	−0.02	0.19 **	0.43 ***	0.09.

4.3. Interaction

We first tried a model with interaction for both length and subsea and AADT HGV and subsea, but then none of the interactions were significant. By only including the interaction between length and subsea, we obtain the results in Table 8:

The predicted number of accidents in tunnel i is now given by $E(Y_i) = t_i e^{\widehat{\beta}_0+\widehat{\beta}_1 s_i+\widehat{\beta}_2 \log L_i+\widehat{\beta}_3 \log A_i+\widehat{\beta}_4 S_i+\widehat{\beta}_5 \log L_i\cdot S_i}$, where s_i, L_i, A_i, S_i are slopes, lengths, AADT HGV and whether or not a tunnel is subsea, respectively. Since $S_i = 0$ for non-subsea tunnels and $S_i = 1$ for subsea tunnels, we interpret these results in the following way:

- The effect of log(Length) in subsea tunnels is the combined effect of log(Length) and log(Length) · Subsea (i.e. $\widehat{\beta}_2 + \widehat{\beta}_5 = 1.06 + 0.93 = 1.99$)
- The effect of log(Length) in non-subsea tunnels is the effect of log (Length) ($\widehat{\beta}_2 = 1.06$)

Notice that the rate of fire accidents increases approximately linearly with length for non-subsea tunnels ($\widehat{\beta}_2 = 1.06$), while it increases approximately quadratically for subsea tunnels ($\widehat{\beta}_2 + \widehat{\beta}_5 = 1.99$). Thus, doubling the length of a non-subsea tunnel should double the rate of accidents, while doubling the length of a subsea tunnel should quadruple the rate of accidents.

AADT HGV also seems to have a greater effect on subsea tunnels in the second model. We will therefore analyze the interaction of AADT HGV and subsea for the second model in a similar way to that for the first model. Since length is an offset in the second model, we will not be able to analyze the interaction of length. Including the interaction of AADT HGV and subsea in Table 5, we get the results in Table 9.

The AIC (Akaike information criterion) measure for goodness of fit is respectively 410.72 and 409.30 for the models reported in Tables 8 and 9, indicating that the model in Table 9 gives the best fit.

Table 8
Model including the interaction seen in Table 6 between length and subsea for the incidents per tunnel model (Model 1); 485 tunnels included.

Variable	$\widehat{\beta}$	p-value	Rate Rate ratio (95% c.i.)
(Intercept)	−2.26	<0.001	–
Slope	0.20	<0.001	1.22 (1.13–1.33)
log(Length)	1.06	<0.001	2.89 (2.25–3.72)
log(AADT HGV)	0.93	<0.001	2.53 (2.14–3.00)
Subsea	−1.02	0.240	0.36 (0.07–1.97)
log(Length) * Subsea	0.93	0.047	2.54 (1.01–6.40)

Table 9
Model including the interaction seen in Table 7 between AADT HGV and subsea for the incidents per length model (Model 2); 485 tunnels included.

Variable	$\widehat{\beta}$	p-value	Rate Rate ratio (95% c.i.)
(Intercept)	−2.26	<0.001	–
Slope	0.21	<0.001	1.24 (1.14–1.34)
log(AADT HGV)	0.87	<0.001	2.38 (1.99–2.85)
Subsea	0.76	0.003	2.14 (1.30–3.53)
log(AADT HGV) * Subsea	0.52	0.027	1.68 (1.06–2.66)

5. Final statistical model

Statistically, the model in Table 9 is the best model and should primarily be used for modelling the rate of fire incidents in Norwegian road tunnels. However, we should also consider the model in Table 8, as it captures the interaction of length and subsea. The models fit the data almost equally well.

When estimating fire accidents in tunnels with distinct tunnel characteristics, and particularly when one variable differentiates substantially from other tunnels in the data material, the models mentioned above will also vary from each another. Estimating fire accidents in the Ryfast tunnel by using the model found in Table 9, we obtained

$$E(Y) = LA^{\widehat{\beta}_3+\widehat{\beta}_5}\ e^{\widehat{\beta}_0+\widehat{\beta}_1 s+\widehat{\beta}_4 S} = 4.05 \tag{6}$$

indicating an estimate of four incidents in the next 15 years.

Estimating fire accidents in the Ryfast tunnel by using the model found in Table 8, we obtained

$$E(Y) = L^{\widehat{\beta}_2+\widehat{\beta}_5} A^{\widehat{\beta}_3} e^{\widehat{\beta}_0+\widehat{\beta}_1 s+\widehat{\beta}_4 S} = 12.91 \tag{7}$$

indicating nearly 13 fire incidents in the next 15 years. Clearly, the predicted number of fire accidents estimated by the two models differs considerably.

The predicted incidents using the model in Table 8 increase approximately quadratically with length. Since the Ryfast tunnel is almost twice the length of the longest tunnel in the data material, we have the same problem as we did with the Lærdal tunnel, only this time due to polynomial growth.

Although both models fit incidents well in the data material, the predictions become problematic when estimating tunnels far away from the data material. We are not sure which model we should trust in such cases.

For a more practical approach, we could also consider using the model in Table 7. Although the interactions are insignificant, it encapsulates all interactions and might, in some cases, give us a better representation of the predicted fire accidents. Estimating fire accidents in the Ryfast tunnel using this model, we obtained

$$E(Y) = L^{\widehat{\beta}_2+\widehat{\beta}_6} A^{\widehat{\beta}_3+\widehat{\beta}_7} e^{\widehat{\beta}_0+\widehat{\beta}_1 s+\widehat{\beta}_5 S} = 8.59 \tag{8}$$

6. Discussion and conclusions

The statistical modelling showed that the key factors influencing fire incidents in road tunnels were *slope, length, annual average daily traffic and whether a tunnel is subsea or not.* These results are in accordance with Nævestad and Meyer's [6] considerations. However, we have modelled the situation using data from all Norwegian tunnels of length >0.5 km. These factors stand out as clearly significant. Moreover, we have been able to evaluate the importance of each factor and how it contributes to fire accidents in road tunnels.

Njå [8] checked all incidents described in Nævestad et al.'s material that included Vision Zero accidents. Three of the ten accidents he scrutinized included erroneous information, which fits well with the findings of Elvik and Mysen [5]. Nævestad et al. improved their data quality process, by involving the relevant road traffic management centers, the tunnel owners' fire protection personnel and various fire and rescue departments responsible for emergency response activities. Thus, Nævestad et al.'s data on incidents is the best we have, and it should give us a reasonable statistical conclusion on fires in HGVs in road tunnels. Going from the general to the specific tunnel project requires considerations beyond the models presented here. Also, going from historical data to forward-looking risk assessment is a challenge for the users of the models. The results found in this work will not automatically generalize to good predictions for the future if unaccounted for important factors change in the future, for instance factors related to the composition of the HGV fleet or improved surveillance of the tunnels.

Using a modelling approach similar to the one we have used, Høye, Nævestad and Ævarsson [26] studied fires and other severe events in tunnels for the period 2008–2015. In addition to looking at a shorter time period, their study differed from ours by looking at fires in all types of vehicles and by including all tunnels and some variables we did not have access to, such as tunnel height, speed limit and curvature. They did not include whether the tunnel was subsea or not. Using length as an adjustment variable (i.e., similar to our Model 2), they found slope to be a main factor for increased fire risk and, moreover, AADT and height to be significant factors, i.e., their results for fire risk in all types of vehicles are similar to our findings for heavy goods vehicles. However, they did not study the effect of subsea tunnels and interaction effects in their models.

Nelisse and Vrouwenvelder [27] introduced a Dutch based model for assigning probabilities, which addresses the input probability ($2.2 \bullet 10^{-9}$ per vehicle km). They used recorded observations of tunnel fires in the Netherlands as the basis for a Bayesian updating. The authors claim that the "real" input probability is more than a factor of 10 lower than in the original model, which they claim is also valid for European tunnels. Based on their views of probabilities in assessments of meeting thresholds related to various categories of fires (HRR), they provide recommendations for risk acceptance. This classical approach to tunnel safety directs the focus away from assumptions and important phenomena involved in tunnel designs and operations exposed to fire occurrences, which we contrast in our use of the fire frequency models.

With the classical Poisson regression model, we have used a well-established objective modelling approach for rare events count data. By enabling overdispersion, this also closely resembles the negative binomial approach used in Høye, Nævestad and Ævarsson [26]. An alternative approach could have been a Bayesian Poisson regression model. Without strong prior knowledge about the key parameters, this would most likely not lead to any major differences, and, if strong prior information were enforced, there would be a discussion about the validity of this information. A benefit of a Bayesian approach is a natural updating procedure if new data becomes available and an update of the model is warranted.

We trust researchers from the risk management field to evaluate and discuss the validity of the models presented. Taking account of this, together with other studies on risk influencing factors, these researchers can make a qualitative decision on which model we should trust, particularly when estimating fire incidents in tunnels like the Ryfast tunnel. Remember, we have produced estimates on fire rates, not for catastrophic fires, as seen for example in the Mont Blanc tunnel in 1999. Such extremely rare events need careful considerations by methods other than those used in the current work.

Declaration of competing interest

There are no conflicts of interests regarding the data and modelling that is used in the study and development of the article submitted to Fire Safety Journal.

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